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Original Article

Vibration Analysis of Frequency Domain Data using MATLAB for Application of Rotating Part Machines in Industry

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Abstract - *Increasing the number of Condition-Based Profitability and safety are given emphasis in monitoring activity. Maintenance is the prevention of anticipated problems by monitoring the machine in time for it to run, which involves process control, keeping the machine operating, logistics, and improvement. This paper focuses on a unique feature of predictive maintenance utilizing the MATLAB tool's State space model, and accuracy is more than 85%. The frequency data is primarily collected from rotating machines using vibrometers, and the obtained spectrums are analyzed using MATLAB for validation, which clearly defines the severity level of vibration in a component and estimates the machine's life by creating a state space model and analyzing it using the asset tool.*

Keywords - *Maintenance, MATLAB, Frequency domain data, Condition monitoring, Vibration analysis.*

1. Introduction

Vibration analysis is an extensively measured parameter in many business programs. Vibration response measurements give valuable information on common issues. The frequency domain data includes both the analytical form and the window. However, frequency domain data have been used in a variety of applications, including nonlinear regression and compression.

The signal is decomposed into time and frequency phrases of a wavelet, known as the mum wavelet, using frequency domain data. Frequency domain data are a powerful statistical tool that may be applied to a wide range of applications, including signal processing, data compression, and business management of gear wheels.

2. Literature Survey

Mazzoleni et al. [1], experimental data are collected for the cylindrical bearing NJ305, and four conditions are considered: inner race defect, outer race defect, roller defect, and healthy bearing. Kurtosis, crest factor, energy, skewness, and other characteristics are calculated for all 900 signals in the database. ANN is trained and tested first for condition auto-identification, and then various classifiers are analysed here to determine the best method. The Support Vector Machine technique as a classifier was found to be the most efficient, with nearly 86% efficiency.

Attoui et al. [5] this paper centres around fostering a convolutional brain organization to gain includes straightforwardly from the first vibration signals and afterwards analyze deficiencies. The viability of the proposed technique is approved through PHM gearbox challenge information and a planetary gearbox test rig which was contrasted with the other three conventional strategies; the outcomes show that the one-layered convolution brain organization (1-DCNN) model has higher exactness for fixed-shaft gearbox and planetary gearbox issue determination than that of the customary indicative ones.

Katipula et al. [8], By comparing the proposed method to previous works, two main contributions are concluded: first, the proposed method directly uses raw vibration signals to carry out fault diagnosis in an end-to-end way, greatly reducing the reliance on human expertise and manual intervention; second, the appropriate network architecture of the MLCNN model is designed to realise compound fault diagnosis of the gearbox effectively and efficiently. Finally, two case studies are used to validate the presented method. The results show that it is more accurate than other existing methods in the literature. Furthermore, its stability performance is quite good.

Li et al. [12], In this research, domain adaptation is employed to facilitate the effective implementations of intelligent fault detection. Specifically, we suggested a framework based on a multilayer multiple kernel form of Maximum Mean Discrepancy. In order to provide consistent findings and enhance accuracy, the kernel approach is developed to replace the high dimensional map of Maximum

Mean Discrepancy. As a result, characteristics from various domains are near one another in the Hilbert Space. Furthermore, two separate domains' characteristics contribute to domain adaptation in each feature layer. Two bearing datasets are utilised to evaluate the suggested method's effectiveness. The experimental findings suggest that the proposed technique can overcome the limits of existing methods and attain conditioned performance.

Pankaj et al. [19], The following methods for CBM fault prognostics are examined in this study: logical data analysis, artificial neural networks, and proportional hazard models. A technique for applying and comparing these models is created, which comprises data pre-processing, model construction, and model output analysis. The outcomes are evaluated using three metrics: error, half-life error, and cost score. According to the findings of this investigation, the LAD and feed-forward ANN models outperform the PHM model. The feedback ANN, on the other hand, performs poorly, with substantially larger variation than the other three approaches' predictions. The purpose of this research is to give suggestions on when and where to employ these three prognostic models based on these findings.

3. Critical Machine Identification

The accelerometer is placed on the motor's non-driving end to collect data using a vibrometer. These measurements were done under full load conditions, and amplitude values in the axial and vertical directions were found to be dominant.

Later, this gathered data is fed into a computer utilising Omnitrend software, where information is transmitted and useful in understanding the prior data and trends, which helps diagnose the problem by verifying whether the readings are within allowed limits. The nature of the problem in equipment is detected by its distinct vibration characteristics.

By studying the vibration amplitude pattern, a localised problem may be identified without affecting the other bearings in the equipment. The details of the Mill fan motor are shown below in Table 1 and identified as high vibration response.

Table 1. Specifications of Mill Fan motor

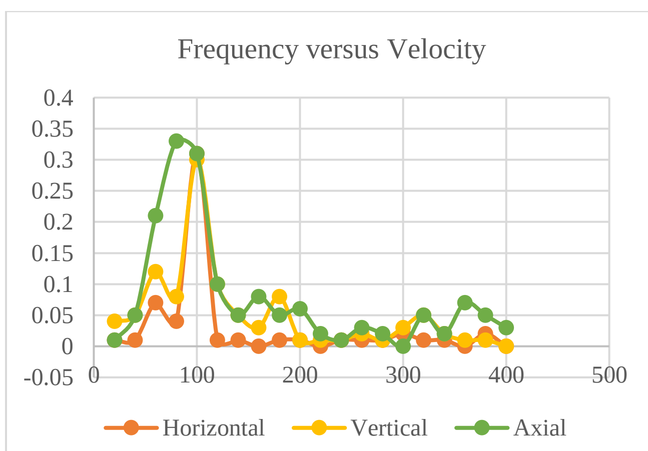
Type of Equipment	Rotor Fan details
Location	Non-Drive End
Pressure	780 MM WC
Impeller diameter	2750MM
Motor	Type 3-Phase
Rating	590Kw
Operating Voltage	7KV
Full Load Current	71 Amp
Motor Speed	990 RPM

Table 2. Data acquisition for Motor Non-drive end

Motor – Non-Drive End (NDE)				
	Frequency	Velocity		
SL NO	X in Hz	V-H	V-V	V-A
1	20	0.01	0.04	0.01
2	40	0.01	0.05	0.05
3	60	0.07	0.12	0.21
4	80	0.04	0.08	0.33
5	100	0.31	0.35	0.31
6	120	0.01	0.1	0.1
7	140	0.01	0.05	0.05
8	160	0.01	0.03	0.08
9	180	0.01	0.08	0.05
10	200	0.01	0.01	0.06
11	220	0.01	0.01	0.02
12	240	0.01	0.01	0.01
13	260	0.01	0.02	0.03
14	280	0.01	0.01	0.02
15	300	0.02	0.03	0.01
16	320	0.01	0.05	0.05
17	340	0.01	0.02	0.02
18	360	0.01	0.01	0.07
19	380	0.02	0.01	0.05
20	400	0.01	0.01	0.03

The data measurements are collected from a variety of sources and analysed to identify equipment failure trends and determine what maintenance is required. Data capture, data manipulation, status detection, health evaluation, and prognosis assessment are all carried out during this stage and are represented in Table 2.

As per the above data collected with triaxial directions for different frequencies, a graph is drawn to show the highest peak to find the fault in the machine. The common type of fault detection is generally categorised into two types: data-driven and model-based approaches.



Graph 1. The graph shows frequency versus velocity with triaxial directions

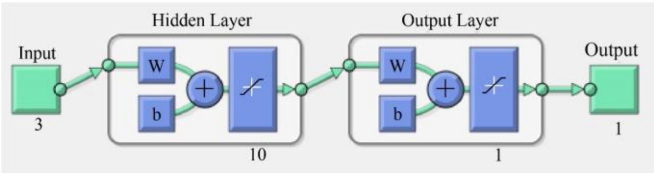


Fig. 1 Neural Network flow diagram

The reason for failure was determined by thoroughly inspecting the sources of bearing problems, such as misalignment, mechanical looseness, and so on, and removing them one by one, which causes bearing failure

4. Neural network

A Neural Network (NN) is a data processing model inspired by how the human brain analyses data. A wealth of material outlines the fundamental architecture and parallels to organic neurons. The material here is restricted to a general overview of the various components involved in the NN implementation. The network design or topology, which includes the number of nodes in hidden layers, network connections, initial weight assignments, and activation functions, is particularly crucial in NN performance and largely relies on the situation at hand. Figure 1 depicts a basic NN and its elements having 3 inputs and 1 output with 10 hidden layers.

An artificial neural network models biological synapses and neurons and can be used to make predictions for complex data sets. Neural networks and their associated algorithms are among the most interesting of all machine-learning techniques.

This paper explains the feed-forward mechanism, which is the most fundamental aspect of neural networks. It is essential to show that the best validation performed at a certain epoch number with a validation value of 88%, which is greater than 85% obtained from training and test data.

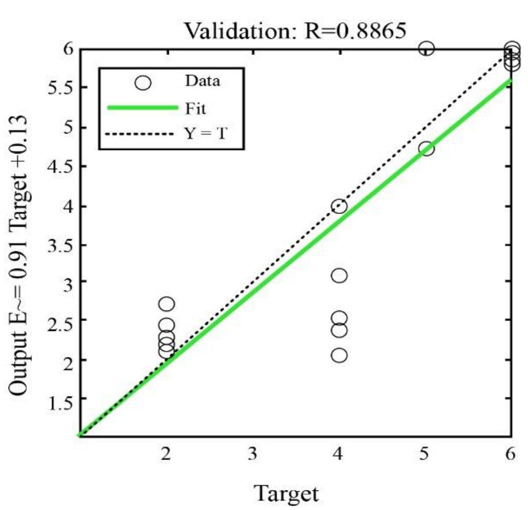


Fig. 2 Validation results showing R-value

5. Validation

Validate the developed regression-based simultaneous bearing fault diagnosis and severity identification methods on a bearing test rig with vibration signals utilizing seeded fault tests.

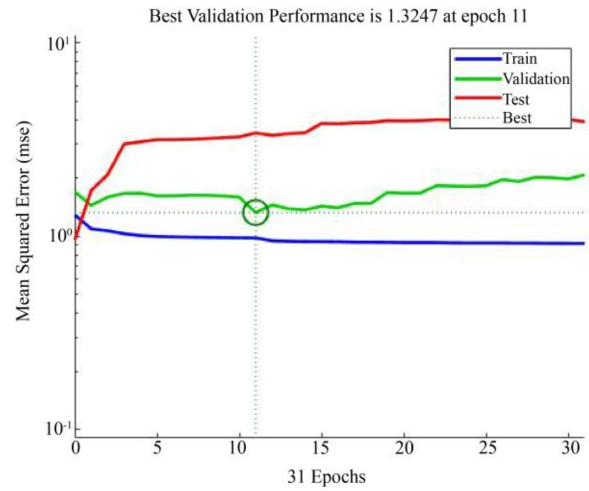


Fig. 3 Performance validation results having MSE and epochs

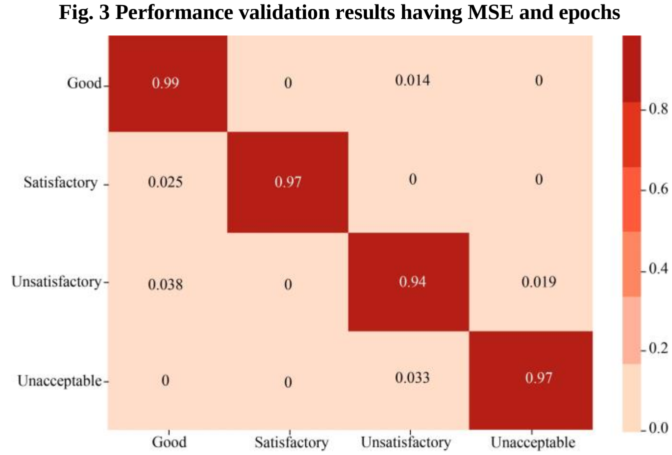


Fig. 4 Forest Qualifier matrix

Figure 3 validates that the best performance validated is 1.3247 at epoch 11. The accuracy of the diagnostic outperforms the previously published values. This study concentrated on imbalance and misalignment since these two flaws are the most typical errors that may be detected in bearing difficulties. Both the unbalance and misalignment rigs have 150000 data points in their data.

The above figure 4 matrix shows the best breakdown error in predictions for unseen data. Each value of the row is standardised by listing different colours with different values. We can easily identify the diagonal values with those of the positions showing the best performance in the matrix. Image classification can be finished with the least error rate.

6. Conclusion

A generic methodology for detecting machinery faults using a pattern recognition technique is proposed. It entails gathering data, extracting features, reducing high-dimensional data, and classifying it using MPL and closest neighbor. Although we utilized bearing fault diagnostics as illustrative examples, the suggested technique may be used in different applications by simply altering the sensory signal properties. This paper concludes towards validation from regression and forest qualifier matrix having more than 85% from literature survey using MATLAB tool for diverging fault detection and prognosis in vibration size techniques for machine factors.

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